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Gearbox Health Condition Monitoring: Vibration Analysis

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***Abstract*—Vibration analysis is a standout amongst the most effective strategies present for diagnosing the health condition of rotating machinery. This paper deals with the vibration based gearbox health condition-monitoring techniques for diagnosing and classifying the gearbox faults. The statistical feature extraction has been done using the discrete wavelet transform whereas the fault classification has been done using support vector machine. The results reveal that these vibration based diagnostic techniques are successful in gearbox health condition monitoring. National Renewable Energy Laboratory (NREL) provided the data used in this paper.**

***Index Terms*— Discrete wavelet transform, Fault diagnosis, Gearbox Health Condition Monitoring, Support Vector Machine, Vibration Analysis.**

I. INTRODUCTION

The engine consists of various modules like fan, compressor, combustor, turbine and exhaust nozzle. All these modules are connected to the shaft using the engine crucial components such as gears and bearings. Health condition monitoring of these engine components is evolving rapidly as one of the important research fields to get efficient operation of the engine. In this paper, vibration-based fault diagnosis and classification algorithms used for gearbox health condition monitoring. Vibration analysis of gearbox has been done using the Wind Turbine Gearbox Vibration Condition Monitoring Benchmarking Datasets, provided by National Renewable Energy Laboratory (NREL) [1].

II. GEARS- THEORY

Gears are the machine components used to change & transmit the rotational motion and torque. In aircraft engines, gears allow the fan as well as the compressor-turbine unit to rotate at different speeds by means of successive engagement of gear teeth. Gear failure happens due to severe stress conditions (When a gear is working under high-stress conditions, there is a tendency to gear failure) [2]. Different types of gears that are used in industries are helical, spur, bevel and worm gears. All these gears have both driven and driving wheels but, differ in shape & wheels arrangement [3].

III. METHODOLOGY

Vibration analysis is a valid and most popular condition monitoring technique used for gearbox fault diagnosis [4]. This technique is sensitive to failure and can provide the continuous health state of the gearbox compared to remaining condition monitoring approaches like oil and temperature analysis [5]. Fig. 1 shows the information flow diagram for vibration based gearbox health condition monitoring technique.

A. Data collection

The data acquisition device (DAQ) can be used for collecting the vibrations produced by the gears with the help of accelerometers mounted on it. The data used in this paper are obtained from National Renewable Energy Laboratory [1]. Eight accelerometers viz., AN3 to AN10 mounted on the gearbox to sense vibratory acceleration. Sensor location, model and description also mentioned in Ref. [1]. The vibration signal has been acquired at a sampling rate/frequency (F_s) of 40KHz. After collecting the gearbox data, the signal is processed to diagnose the faults.

B. Signal Preprocessing

Preprocessing is required to eliminate the artifacts/noise from the raw vibration signal.

C. Feature Extraction

It is a process/method to obtain meaningful and important characteristics from the signal by transforming it to set of features. Feature extraction can be done in three ways. They are time domain, frequency domain and time-frequency domain analysis. In this paper, a time-frequency domain analysis approach called discrete wavelet transform (DWT) [6, 7] have been used to extract the features.

DWT decompose the signal into a mutually perpendicular set of wavelets and is extensively used for multiresolution signal analysis. Therefore, vibration signal is decomposed into 12 levels and variance of these 12 levels detailed coefficients viz., D1 to D12 and approximation coefficient (A) have been computed.

D. Feature Selection

With the thirteen features (A, D1, D2,…, D12) extracted from DWT, a feature vector have been formed to diagnose the gearbox faults.

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E. Fault Classification

For classifying the faults, a set of algorithms used such as Support Vector Machines (SVM), Artificial Neural

Networks (ANN), K-Nearest Neighbors (KNN)… etc. SVM have been used for classification in this paper. The feature vector formed by the useful features has been used to train the SVM (Support Vector Machine) classifier [8] for classification of gearbox faults.

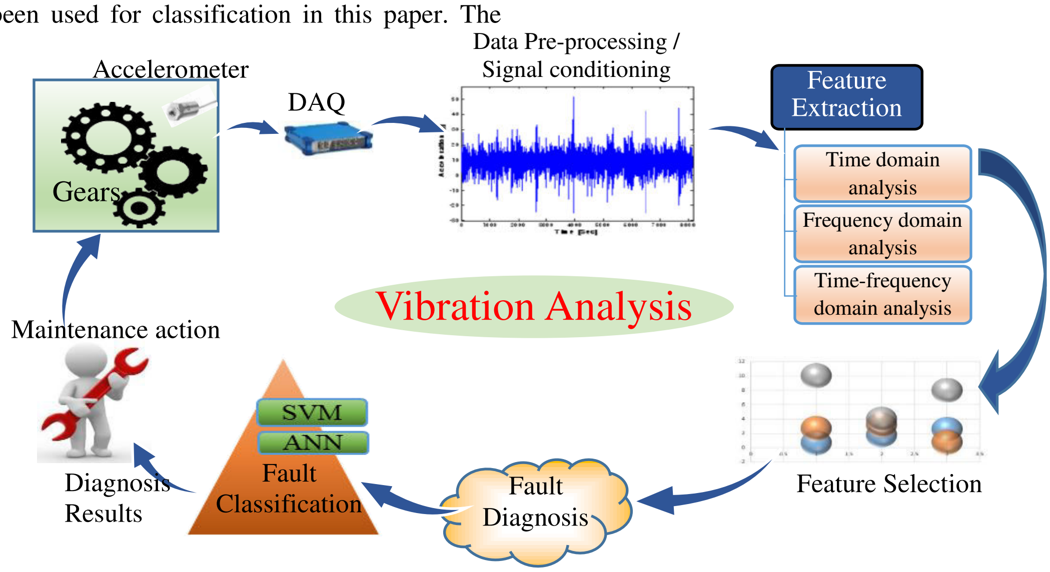

Fig. 1. Proposed methodology for gearbox health condition monitoring

IV. Results And Discussions

Thirteen features viz., A, D1, D2,…, D12 for each individual sensor from AN3 to AN10 are shown in Fig. 2. It can be observed that the features have larger magnitude for damaged gearbox data than healthy gearbox data. It can also be observed that most of the features have been succeeded in the detection of healthy and damaged conditions. The mean ± standard deviation of these features for all the sensors is shown in Table I.

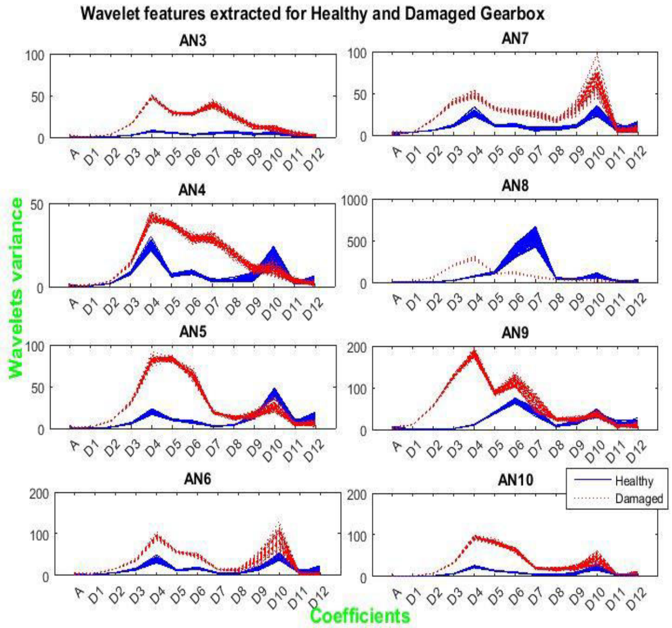

Fig. 2. Wavelets variance for healthy and damaged gearbox data

Fig. 3 shows the gearbox fault classification with SVM classifier using features D11 and D12. It can be observed that healthy and damaged gearbox vectors have been completely overlapped. Hence, misclassification happened and the poor classification region is marked in the circle. Therefore, there is no clear classification between the faults by choosing these features.

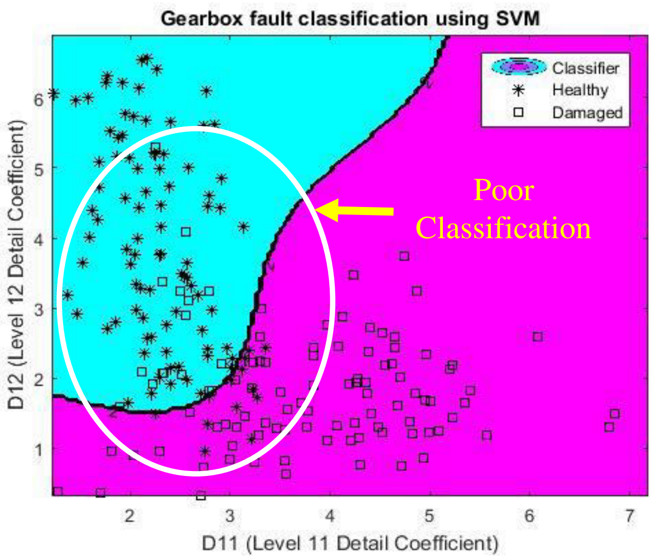

Fig. 3. SVM classification using D11 and D12 coefficients Variance

The SVM classifier for A and D1 features is shown in Fig. 4. It can be observed that the classifier fails to classify few samples of healthy and damaged gearbox data as marked in Fig. 4. Therefore, these features are moderately classifying the gearbox faults.

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F	AN3		AN4		AN5		AN6		AN7		AN8		AN9		AN10	
	HG	*DG*	*HG*	*DG*	*HG*	*DG*	*HG*	*DG*	*HG*	*DG*	*HG*	*DG*	*HG*	*DG*	*HG*	*DG*
A	0.2275 ± 0.1214	0.7571 ± 0.3824	0.2299 ± 0.1243	0.6552 ± 0.3375	0.5458 ± 0.2459	0.9181 ± 0.5191	1.2065 ± 0.6066	3.3250 ± 1.0959	0.7787 ± 0.4447	2.3191 ± 0.8194	4.9158 ± 2.0870	1.1109 ± 0.6091	2.0361 ± 1.1881	1.9517 ± 1.2719	0.2847 ± 0.1442	1.2531 ± 0.5049
D1	0.1530 ± 0.0080	0.5723 ± 0.0151	0.4275 ± 0.0181	0.7404 ± 0.0317	0.3208 ± 0.0108	1.4172 ± 0.0758	2.5200 ± 0.0525	4.7912 ± 0.3156	3.4853 ± 0.0757	3.4241 ± 0.2272	0.9011 ± 0.0293	9.0570 ± 0.6097	0.0443 ± 0.0060	11.0841 ± 0.5310	0.3938 ± 0.0146	1.1992 ± 0.0415
D2	0.6808 ± 0.0287	3.4323 ± 0.0752	1.8801 ± 0.0798	3.6453 ± 0.2952	1.3506 ± 0.0725	8.5979 ± 0.4233	6.9294 ± 0.1915	15.0876 ± 1.1302	5.6575 ± 0.1219	17.5817 ± 1.0929	5.0031 ± 0.1775	53.2609 ± 3.8804	0.3430 ± 0.0463	54.7211 ± 2.2074	1.7554 ± 0.0756	7.6422 ± 0.2524
D3	2.3822 ± 0.1593	16.225 ± 0.4888	8.0139 ± 0.4783	15.999 ± 1.7525	5.8606 ± 0.4652	30.8988 ± 1.0624	14.815 ± 0.9702	34.3669 ± 2.8056	11.1004 ± 0.5924	38.1653 ± 1.9214	21.0867 ± 1.1031	177.315 ± 15.0063	2.4388 ± 0.3230	128.687 ± 2.8456	6.9473 ± 0.4453	32.7192 ± 1.0713
D4	7.1876 ± 0.5796	50.5071 ± 1.9783	25.168 ± 1.6613	43.9459 ± 2.5689	19.1474 ± 1.6820	81.8606 ± 2.9139	36.2803 ± 3.3440	85.5606 ± 7.8938	26.6282 ± 2.0505	45.8028 ± 2.7604	69.8170 ± 4.0268	263.439 ± 16.6194	13.3740 ± 1.6000	186.443 ± 6.6053	23.7362 ± 1.6087	93.5075 ± 3.3802
D5	5.4685 ± 0.3585	30.3765 ± 1.2644	6.5162 ± 0.5034	37.6879 ± 1.1812	9.8116 ± 0.4630	82.1621 ± 1.9537	11.8499 ± 0.682	55.2967 ± 2.1185	10.9584 ± 0.6496	31.7391 ± 1.3230	114.992 ± 7.8567	108.640 ± 3.2020	44.7519 ± 3.3576	90.4138 ± 3.6987	13.5269 ± 0.8187	82.7891 ± 2.8695
D6	2.8490 ± 0.2853	28.1264 ± 1.2046	8.6963 ± 0.6611	27.3841 ± 1.6290	7.3198 ± 0.6150	60.4370 ± 3.6994	16.7717 ± 1.3269	44.7699 ± 3.6332	11.1465 ± 0.9858	26.9769 ± 1.4512	371.295 ± 41.5093	108.973 ± 6.5468	69.9763 ± 3.5902	116.554 ± 9.4042	9.6438 ± 0.7017	61.3101 ± 3.7262
D7	4.7910 ± 0.5166	39.2156 ± 2.8501	3.3727 ± 0.4596	28.4114 ± 1.8640	2.3291 ± 0.3527	19.9957 ± 1.5611	5.7947 ± 0.6076	13.7286 ± 0.9996	6.5639 ± 1.0968	25.8967 ± 2.3241	529.232 ± 58.7680	59.5544 ± 5.7913	39.9421 ± 4.4502	57.8479 ± 12.5309	5.2185 ± 0.5030	20.5704 ± 1.6354
D8	5.9372 ± 0.6477	25.1100 ± 2.3644	3.5311 ± 0.4906	19.6788 ± 1.6970	3.6852 ± 0.3822	12.3970 ± 1.8432	5.1140 ± 0.5725	12.9348 ± 1.7589	7.5278 ± 1.1918	18.2374 ± 1.8651	45.2877 ± 3.8284	36.1166 ± 4.0360	7.7666 ± 0.9861	24.4225 ± 2.6621	4.0901 ± 0.7088	18.1544 ± 3.1592
D9	3.4685 ± 0.6162	12.5119 ± 1.8736	5.9497 ± 1.3855	10.2976 ± 1.5901	14.0785 ± 1.1688	15.3568 ± 2.8836	16.9593 ± 1.9558	38.7317 ± 7.4553	10.2570 ± 1.1834	30.8680 ± 4.5936	38.4616 ± 5.0313	19.1569 ± 3.4943	17.3802 ± 2.2836	23.2279 ± 3.6959	7.7023 ± 1.2823	20.2729 ± 3.9366
D10	5.0998 ± 0.8017	10.6367 ± 2.6197	16.5956 ± 3.3660	10.7474 ± 2.4219	42.4103 ± 2.7762	25.6327 ± 4.6040	44.2906 ± 4.6885	81.9085 ± 17.4621	29.3453 ± 2.8065	64.0179 ± 10.4165	76.2027 ± 10.6621	20.0914 ± 4.5095	39.6413 ± 4.2309	36.2096 ± 4.7162	21.9692 ± 3.1299	41.5993 ± 8.0105
D11	1.5110 ± 0.4298	4.5727 ± 1.3597	2.3081 ± 0.5219	3.6679 ± 1.0979	7.4643 ± 1.4039	5.1696 ± 1.2731	9.1331 ± 2.1894	3.6855 ± 1.0877	7.2221 ± 2.0287	5.6761 ± 1.4694	14.7461 ± 4.5470	7.1663 ± 2.3357	11.3958 ± 3.0974	8.2808 ± 2.2511	3.1100 ± 0.6556	4.1992 ± 1.1306
D12	1.1058 ± 0.4988	1.9319 ± 0.8605	3.8066 ± 1.5930	1.7707 ± 0.7777	11.2065 ± 4.3012	5.7995 ± 2.3505	11.7018 ± 4.8414	4.3114 ± 1.8650	8.0789 ± 3.2624	6.0659 ± 2.3060	13.8821 ± 5.2143	4.4268 ± 1.9557	12.1913 ± 5.1523	9.4717 ± 3.9200	5.2146 ± 2.0484	6.3469 ± 2.8520

TABLE I. MEAN ± STANDARD DEVIATIONS OF WAVELETS VARIANCE

Note: Here F represents Features, HG means Healthy Gearbox, DG means Damaged Gearbox and AN3 to AN10 are the sensors mounted on the Gearbox [1].

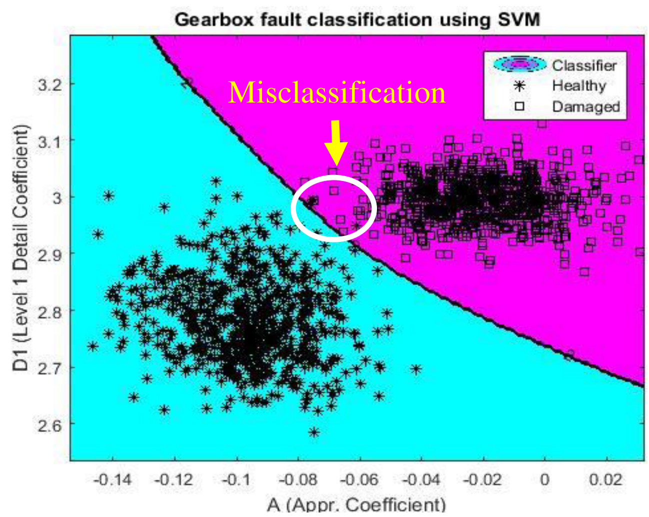

Fig. 4. SVM classification using A and D1 coefficients variance

SVM classification using features D9 and D10 is shown in Fig.6. It can be observed that both healthy and damaged gearbox data are clearly classified using these features.

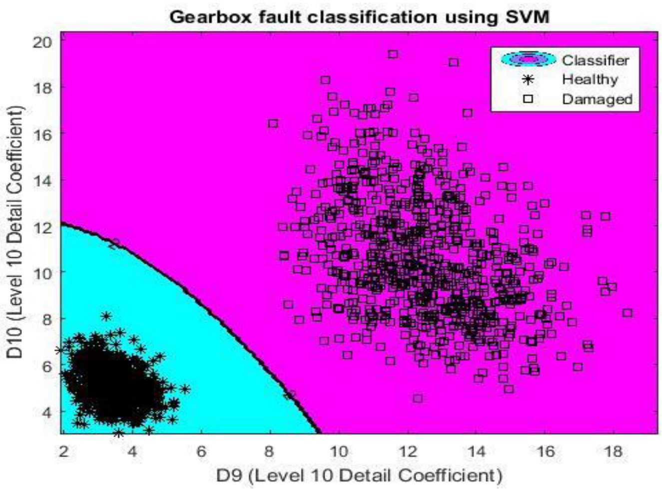

Fig. 5. SVM classification using D9 and D10 coefficients variance

Table II represents all the features with their usefulness in classifying the gearbox faults. The features marked with green color are very useful for gearbox fault classification using SVM classifier. Similarly, the features that are shown with yellow color are marginally classifying the faults. Remaining wavelet features that are shown with white color in Table II are not useful features for fault classification.

TABLE II. USEFULNESS OF FEATURES

Features	Wavelets Variance							
	AN3	*AN4*	*AN5*	*AN6*	*AN7*	*AN8*	*AN9*	*AN10*
A	✓	☑	×	✓	✓	✓	×	✓
D1	✓	✓	✓	✓	×	✓	✓	✓
D2	✓	✓	✓	✓	✓	✓	✓	✓
D3	✓	✓	✓	✓	✓	✓	✓	✓
D4	✓	✓	✓	✓	✓	✓	✓	✓
D5	✓	✓	✓	✓	✓	×	✓	✓
D6	✓	✓	✓	✓	✓	✓	✓	✓
D7	✓	✓	✓	✓	✓	✓	✓	✓
D8	✓	✓	✓	✓	✓	✓	✓	✓
D9	✓	✓	×	✓	✓	✓	☑	✓
D10	✓	✓	✓	✓	✓	✓	×	✓
D11	✓	☑	☑	✓	×	✓	×	×
D12	×	☑	☑	✓	×	✓	×	×

Note: Here, ✓ represents clear or perfect classification, ☑ moderate classification and × represents very poor classification.

V. CONCLUSION

This paper deals with vibration analysis based gearbox health condition monitoring. DWT had been used to extract the wavelet variance features from the vibration data. SVM classifier had been used to classify healthy and damaged data. The useful features for gearbox fault diagnosis had been presented. The results reveal that the vibration based condition monitoring technique is successful in diagnosing and classifying the gearbox faults. This condition monitoring algorithm is simple and can be used for real time applications as well.

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